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ABSTRACT

The use of multivariate statistics in behavioral research is investigated, with emphasis on the reasons why multivariate methods can be so important. The concepts of testwise and experimentwise error are explained, and it is noted that multivariate methods can be used to control the inflation of experimentwise Type I error. It is also noted that multivariate methods can detect effects that would go unnoticed in univariate analyses; a small data set is used to illustrate this possibility. Finally, it is noted that multivariate methods often best honor the reality about which the researcher is attempting to generalize. Two tables present a hypothetical data set for eight cases, and separate analysis of variance results for two dependent variables across two levels of an independent variable, respectively. (Author/SLD)

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Why multivariate statistics are critical:

A review with examples

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ABSTRACT

Researchers are increasingly recognizing that the use of multivariate statistics can be vital in behavioral research. This paper explores the several reasons why multivariate methods can be so important. The concepts of testwise and experimentwise error are explained, and it is noted that multivariate methods can be used to control the inflation of experimentwise Type I error. It is also noted that multivariate methods can detect effects that would go unnoticed in univariate analyses; a small data set is used to illustrate this possibility. Finally, it is noted that multivariate methods often best honor the reality about which the researcher is attempting to generalize.

Because human behavior has multiple facets, and each facet is so often affected by a wide range of variables, many behavioral studies ask questions that involve both multiple independent and multiple dependent variables. In such instances, the use of univariate methods is inappropriate for attempts to answer complex empirical questions that should consult the full network of all possible relationships among the system of relevant variables. As a result, there is increasing recognition by social scientists that multivariate techniques are often critical in behavioral research. The term "multivariate" is commonly used to describe statistical methods that simultaneously test effects involving two or more dependent variables.

Huberty and Morris (1989) discuss three types of research questions that only multivariate statistics can address. Since outcome variables are usually interrelated, and since these relationships can have extremely dramatic influences on results and interpretations, thoughtful researchers often wish to use analytic methods that consider all the correlations among the variables. Only through the use of multivariate methods can outcome variable subsets and important latent structural dynamics be identified. These outcome variable intercorrelations can then be used in a variety of ways to describe a given data set by determining the relative contribution made by each outcome variable to the overall effect. Subset identification and variable effect contributions make it possible to determine if an emerging pattern represents an important underlying construct.

This paper reviews some of the most common challenges faced by social science researchers and the manner in which multivariate methods meet these challenges. The first problem is the one posed by the **inflation of experimentwise Type I error rates.** Another problem involves the **possible failure to detect true effects** that may be otherwise statistically significant. Maintaining the integrity of the variable relationships that define behavior and thus **honoring the complex nature of the reality being investigated** is another important consideration. After these considerations are explained, some of the more commonly used multivariate methods will be briefly described.

EXPERIMENTWISE TYPE I ERROR CONTROL

One important reason for the use of multivariate statistics is to afford protection against the Type I error rate inflation that usually occurs in studies that test two or more dependent variables. There are two kinds of Type I errors associated with any experiment. "Testwise" error is the error associated directly with each hypothesis tested. Most researchers control for testwise error by the selection of a low alpha value prior to analysis. This selected alpha is equal to the testwise error.

But for a given set of data, any number of hypotheses may be tested. Each <u>specific</u> hypothesis has a testwise error rate, as just noted. There is also an "experimentwise" error rate associated with any study. This is the probability of having made one or more Type I errors somewhere within the entire experiment <u>as a whole</u>.

Fish (1988) notes that testwise and experimentwise rates can be equal under two conditions. When only one hypothesis is tested, the two rates are the same. When two or more hypotheses are tested using perfectly correlated dependent variables, the rates are again the same, since only one hypothesis is actually being tested. Under any other circumstances, the experimentwise error rate will have a higher value than the testwise rate. Conducting a series of univariate analyses in a given study testing perfectly uncorrelated dependent variables will result in exponential increases in experimentwise error rate. For example, if a researcher performs five perfectly uncorrelated tests each at the 0.05 level (as perhaps in a classical ANOVA investigating omnibus tests), the experimentwise error rate will be:

$$\begin{aligned} \text{EW Type I Error} &= 1 - (1 - 0.05)^5 \\ &= 1 - (0.95)^5 \\ &= 1 - 0.77378 \\ &= 0.226219 \end{aligned}$$

As Thompson (1988) points out, the exact experimentwise error rate in studies cannot be determined by the researcher unless the dependent measures are either perfectly correlated or perfectly uncorrelated. The rate in such cases will lie somewhere within a range between the testwise error rate and a mathematically determined ceiling, but the exact value will be unknown--this in itself will (and should) be disturbing to some researchers. When multivariate statistics are used rather than a series of univariate analyses, the separate hypothesis tests become a unified test of

a single hypothesis. This equates the experimentwise error rate with the testwise error rate, thus controlling the inflation of Type I error rates.

FAILURE TO DETECT STATISTICALLY SIGNIFICANT EFFECTS

Although inappropriate usage of univariate techniques can lead to the mistaken rejection of the null hypothesis, paradoxically such usage may also result in the failure to detect effects that may have been statistically significant had multivariate methods been used instead (Maxwell, in press). Using a hypothetical data set, Fish (1988) presents a concrete example illustrating how this may occur. Table 1 presents a data set in which "X" and "Y" represent the two dependent variables tested across two levels of the independent variable "B". The results of the ANOVA's conducted separately on each dependent variable are shown in Table 2.

INSERT TABLES 1 AND 2 ABOUT HERE.

After the results are analyzed, two pieces of information are examined, the critical test value and effect size. In the example shown in Table 2, neither the p value for "X" (p_{calc}=.12) nor the p value for "Y" (p_{calc}=.59) are statistically significant at the .05 level. Consideration of effect sizes (the correlation ratio for this example) also leads to the conclusion that the independent variable contributed little to the variation in either dependent variable. The researcher responsible for conducting this hypothetical study would fail to reject the null hypothesis in

either analysis.

Using multivariate analysis of variance (MANOVA) in this particular situation, however, would result in a different statistical conclusion being drawn by the investigator. One of the critical features of multivariate analyses, including MANOVA, is the sensitivity of the method to the intercorrelations among the dependent measures, which are ignored in univariate methods (Maxwell, in press). A MANOVA conducted on the same data set would result in rejection of the null hypothesis (F=9.62; df=2,29; p<.001).

The multivariate effect size estimator in this example is a statistic called lambda, which is akin to the univariate sum of squares error divided by the sum of squares total. Lambda can be conceptualized as the amount of dependent variable variance (0-100%) unexplained by the independent variable(s). With mathematical limits of zero and one, the closer lambda is to zero, the stronger the effect size is. For this example, lambda is 0.601, thus indicating the variable "B" actually explains 40% of the dependent variable variance when "X" and "Y" are considered as a set. This example illustrates that the use of multivariate methods can prevent false statistical conclusions from being drawn.

ACCURATE REPRESENTATION OF REALITY

Because statistical significance is meaningless without a sound underlying theoretical basis, the most important reason for using multivariate statistics is to acknowledge the integrity of

all variable relationships in a manner that best reflects reality. The factors shaping behavior--physiological, sociological, and environmental--are not independent of each other; these factors all contribute to behavior. A univariate study is incapable of addressing the complexity of the full network of variable relationships, which may to distorted pictures of reality (Fish, 1988).

Additionally, in social science research, several observed variables may together represent an underlying "synthetic" variable that cannot be directly observed (Dillon & Goldstein, 1984). By reducing a potentially large number of variables into a few synthetic variables, a more parsimonious and meaningful explanation of behavior may result. The ability to tap into these underlying constructs would be lost without multivariate techniques.

CONCLUSION

Hinkle, Wiersma and Jurs (1979, p. 415) noted that "it is becoming increasingly important for behavioral scientists to understand multivariate procedures even if they do not use them in their own research." Thompson (1986, p. 9) notes that the reality about which most researchers wish to generalize is usually one "in which the researcher cares about multiple outcomes, in which most outcomes have multiple causes, and in which most causes have multiple effects." Tatsuoka's (1973, p. 273) previous remarks remain telling:

> The often-heard argument, "I'm more interested in

> seeing how each variable, in its own right, affects the outcome" overlooks the fact that any variable taken in isolation may affect the criterion differently from the way it will act in the company of other variables. It also overlooks the fact that multivariate analysis--precisely by considering all the variables simultaneously--can throw light on how each one contributes to the relation.

Although it has been shown that multivariate techniques are often critical for use in behavioral research, many researchers avoid their use. Bernstein (1988) cites the difficulty of usage inherent in the traditional calculation of these techniques, although the increased availability of computerized statistical packages simplifies usage and reduces the amount of time otherwise required. The lack of understanding regarding multivariate methods is a reason discussed by Fish (1988), who suggests several sources for the researcher who wishes to correct this deficiency.

But statistical packages and knowledge of the techniques alone are no substitute for thoughtful evaluation and understanding of the theories that underlie measurements. Bernstein (1988, p. 13) advises the investigator to "be aware of the theories guiding your work... No statistical wizardry can substitute for what you know about the phenomena you are studying."

Multivariate statistics have been shown to control for experimentwise Type I error rate. These same methods can also reveal statistically significant effects that univariate analyses

may miss. Statistical significance and effect size provide an index for the investigator to decide if the analyzed relationships have practical significance. Accurate interpretation within a theoretical framework and development of meaningful constructs should be the goal in any study. It is within this context that more researchers should consider the critical contribution multivariate statistics can make in behavioral research.

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Table 1
Hypothetical Data Set from Fish (1988)

Case	B	X	Y	Case	B	X	Y	Case	B	X	Y	Case	B	X	Y
1	1	4	2	9	1	6	6	17	2	1	2	25	2	6	6
2	1	5	3	10	1	8	6	18	2	3	3	26	2	6	6
3	1	4	4	11	1	7	6	19	2	3	5	27	2	6	7
4	1	4	5	12	1	9	7	20	2	3	5	28	2	7	7
5	1	3	4	13	1	8	7	21	2	2	5	29	2	7	7
6	1	6	5	14	1	8	8	22	2	4	6	30	2	8	9
7	1	5	6	15	1	9	8	23	2	4	5	31	2	8	9
8	1	7	5	16	1	9	9	24	2	5	6	32	2	9	9

Table 2
Separate ANOVA Results for the Two Dependent Variables
(Fish, 1988)

Source	SOS	df	MS	Fcalc	pcalc	Effect Size
B	12.5	1	12.50	2.6	0.12	7.9%
Error	145.5	30	4.85			
Total	158.0	31	5.10			
B	1.1	1	1.12	0.3	0.59	1.0%
Error	112.4	30	3.75			
Total	113.5	31	3.66			